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Bayesian model for identifying true positions of surface-to-air missile systems for survivability assessment

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Abstract
Background/Aim: the survivability assessment of surface-to-air missile (SAM) systems is widely conducted using methodologies based on the P_{kill} concept (probability of kill) and its derivatives adopted by NATO Headquarters. One of the key components of this methodology is the probability of correct identification of the SAM system position. The implementation of counter-reconnaissance measures, in particular the deployment of decoy positions, introduces substantial uncertainty into the process of identifying detected positions. **Methods:** a combined approach is proposed for estimating the probability of correct position identification, integrating Bayesian inference with a bootstrap method for generating additional data samples under various tactical scenarios. Bootstrap samples are generated from the initial observation datasets for each position, enabling the incorporation of both prior information on the existence of a true position and updated information obtained through repeated reconnaissance. **Results:** the proposed approach provides not only point estimates of the probability of detecting a true SAM position but also corresponding confidence intervals and an assessment of model robustness to data fluctuations. The results demonstrate that traditional approaches relying solely on prior information are inadequate and lead to overestimated expectations regarding the effectiveness of counter-reconnaissance measures. **Conclusion:** the developed model enables simulation of an adversary's SAM position identification process in the absence of reliable information about its reconnaissance algorithms or intelligence sources. To improve the reliability of the estimates, it is advisable to conduct field experiments in rear areas by establishing a notional position area with multiple false positions and performing repeated reconnaissance.

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1. Introduction

Under the conditions of the full-scale war of the Russian Federation against Ukraine, the survivability of air defense assets, and surface-to-air missile (SAM) systems in particular, is a critically important component of their combat effectiveness.

The experience of contemporary armed conflicts, particularly the Russian-Ukrainian war, confirms that the widespread employment of unmanned aerial vehicles (UAVs), precision-guided munitions, and integrated reconnaissance-strike systems significantly increases the probability of rapid detection and engagement of air defense asset positions. Open-source analytical studies indicate that persistent battlefield surveillance conducted by UAVs, combined with the timely updating of target designation data, renders SAM positions that are not protected by comprehensive measures of concealment, deception, and decoy deployment highly vulnerable [1-4].

Under such conditions, the establishment of false positions, the use of multispectral camouflage measures, thermal and radar simulators, as well as the integration of these measures with electronic warfare assets (to complicate reconnaissance and the identification of real targets), become critically important for enhancing SAM survivability. An analysis of tactical developments after the third year of the Russian-Ukrainian war demonstrates that both sides actively employ clusters of prepared positions, including false positions, as well as fortified shelters, in order to create uncertainty regarding the location of actual positions. This creates the need to refine methods for assessing the probability of correct identification of SAM positions under conditions of information uncertainty arising from the combined effects of physical concealment, operational deception, and electronic countermeasures [1-2].

For the assessment of the survivability of air defense assets, and surface-to-air missile systems in particular, the survivability assessment methodology based on the P_{kill} [5] concept is widely applied in NATO headquarters and

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within the Armed Forces of Ukraine. This approach is traditionally used to determine the probability that any air defense element transitions to a non-operational state as a result of fire damage. During combat operations in Ukraine, countermeasures aimed at opposing enemy reconnaissance and fire engagement on the battlefield are implemented to enhance the protection and concealment of primary SAM positions. These measures include, in particular, the establishment of false positions equipped with SAM mock-ups and simulated activity. Such actions create a state of information uncertainty for the adversary, significantly complicating the processes of target identification and selection.

The assessment of the probability of correct identification of a true SAM position under these conditions becomes particularly relevant, as it directly affects the calculation of P_{kill} and, consequently, the evaluation of combat effectiveness. At the same time, traditional methodologies do not always account for the dynamic evolution of probabilities arising from repeated observations and continuous updates of intelligence data.

In modern reconnaissance, tracking, and target engagement systems, the object identification problem is treated as a Bayesian hypothesis recognition task, in which each hypothesis corresponds to a specific class or a possible target state, while available intelligence data are represented as an observation vector. The posterior probability is interpreted as a quantitative measure of the plausibility that a given hypothesis is true in light of the acquired information. This approach constitutes a standard tool in radar target recognition, electronic intelligence, and multisensor information fusion.

Fundamental works on pattern recognition theory and statistical decision-making, in particular [6], demonstrate that the optimal decision regarding class or hypothesis selection in the presence of interference, noise, and feature overlap is based on maximizing the posterior probability. Similar Bayesian principles underpin modern multisensor tracking and object identification methods employed in military systems [7].

Within these approaches, observations may include radar signatures, emission parameters, thermal and optical features, as well as any other intelligence information used to distinguish between different target types or object states. Bayes' theorem enables the systematic combination of prior assumptions regarding possible hypotheses with updated observational data, yielding posterior estimates that are directly applied in decision-making. However, in most classical Bayesian models for target recognition and tracking, hypotheses typically do not account for the presence of deliberately created false objects or positions intended to deceive the adversary.

In the context of SAM survivability assessment, this implies that false positions imitating real SAM systems are usually not treated as separate competing hypotheses within the Bayesian framework, leading to a simplified and potentially overestimated assessment of the probability of correct identification of the true position.

This circumstance necessitates an extension of the classical Bayesian formulation of the identification problem by explicitly incorporating true and false SAM positions as alternative hypotheses, thereby enabling a quantitative evaluation of the effects of camouflage and deception in survivability assessment within the P_{kill} methodology.

The assessment of survivability and combat effectiveness of surface-to-air missile systems constitutes one of the key tasks of modern defense analysis. This issue is particularly relevant under conditions of rapid evolution of air attack and reconnaissance assets, as well as the employment of precision-guided munitions capable of engaging targets with a first strike. In NATO and U.S. doctrinal documents, survivability is defined as the property of an object to maintain its functional state under the influence of combat and abnormal factors [8], [9]. In well-known scientific studies, in particular [5], the probability of target neutralization, P_{kill}, is used as a quantitative measure of strike effectiveness and is defined as the product of sequential probabilities of detection, correct identification, launch execution, hit, and kill. The baseline P_{kill} approach represents a standard for assessing the vulnerability of air defense assets; however, it exhibits limitations associated with the assumption of static input probabilities. Under real combat conditions, intelligence information evolves dynamically, and therefore traditional assessments often fail to account for updated data regarding the authenticity or falsehood of targets.

In the scientific and technical literature, studies on the survivability and combat effectiveness of air defense assets encompass a wide range of approaches, from vulnerability analysis of individual components to the assessment of the resilience of complex systems. Considerable attention is devoted to modeling scenarios of massed strikes and countermeasure activities. In particular, study [10] proposes an adaptive fuzzy threat assessment method for air defense systems, which enables rapid adjustment of model parameters to specific battlefield conditions. Such an adaptive threat assessment can be integrated into SAM survivability evaluation models. The method demonstrates the feasibility of combining expert judgment with automated model tuning under combat conditions.

Issues of resilience and recoverability are addressed in [11], where a method for assessing the resilience (robustness and recovery capability) of aerospace defense systems is proposed based on kill-network theory and an enhanced self-information metric that accounts for nodes and links, integrating survivability, recoverability, and risk response assessment. The paper provides an example of an integrated effectiveness assessment that considers both combat capabilities and the ability to rapidly recover after an attack.

Paper [12] addresses the problem of enhancing survivability and robustness of Weapon System of Systems (WSoS), which represent a set of heterogeneous weapon systems interacting to accomplish common missions. The authors emphasize that under modern combat conditions, a key requirement is the combination of high system resilience with minimized costs for system development and modernization. The study develops an algorithm for the quantitative assessment of WSoS survivability under vari-

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ous attack strategies and reconfiguration scenarios. In addition, an economic model is formulated that accounts for the costs of procuring new equipment, upgrading existing systems, and expenditures associated with resilience enhancement. Based on these approaches, an optimization model is constructed to balance survivability indicators and associated costs.

Ukrainian scientific research has made a significant contribution to the development of methodologies for assessing the survivability of weapons and military equipment. In study [13], a method for determining survivability characteristics is proposed, based on the analysis of resistance to damage under combat conditions, taking into account design, organizational-tactical factors, and probabilistic indicators. A methodology for assessing the survivability of anti-aircraft weapons considering the dynamics of modern combat, various enemy strike options, and survivability enhancement measures is presented in [14], enabling its application in staff-level planning of combat operations.

In study [15], a generalized probabilistic model for assessing the survivability of armored vehicles is developed, describing the damage process as a sequence of interrelated events, from detection to loss of combat capability. The model integrates indicators of reliability, protection, resistance to damage, and recoverability, and can be adapted for the survivability assessment of SAM systems. A set of practical survivability enhancement measures, including the creation of false positions, maneuvering, and camouflage, is considered in [16], where their impact on reducing the probability of detection and engagement of SAM systems is demonstrated.

Issues related to improving the objectivity of survivability assessment for air defense missile units under modern conditions are addressed in [17], where it is proposed to consider not only the fact of damage but also the degree of preservation of functional capabilities after partial damage. In study [18], a methodology for determining the optimal number of false launch positions is developed, taking into account the probability of detecting true positions and resource constraints, which is directly related to survivability enhancement tasks in defensive operations.

Methodologies for assessing the survivability of artillery and radiotechnical units, considering the probabilities of detection, engagement, and recovery, are presented in [19] and [20], confirming the universality of the probabilistic approach across different branches of the armed forces.

Among works addressing the application of the Bayesian approach in military-applied problems, study [21] deserves special attention, proposing a decision-support model based on a dynamic Bayesian network for the quantitative assessment of battlefield uncertainty. The study demonstrates the feasibility of integrating heterogeneous intelligence information and forecasting adversary actions, which is fundamentally important for survivability assessment under conditions of information uncertainty.

Thus, contemporary scientific research demonstrates a broad range of survivability assessment methods for weapon systems, from the classical P_{kill} approach to integrated probabilistic and statistical models that account for the dynamics of the operational environment and the uncertainty of intelligence data. At the same time, there remains a need for comprehensive approaches that combine tactical aspects (deployment, camouflage, deception), equipment reliability, and mathematical analysis methods adapted to wartime conditions. It is particularly relevant that during combat operations intelligence information is continuously and dynamically updated, influencing decisions on strikes against SAM positions. Therefore, the search for new approaches to assessing the survivability and effectiveness of SAM systems, taking into account both prior and updated information used in decision-making processes, remains of high importance.

Taking these considerations into account, this study further proposes the development of a combined approach for assessing the probability of correct identification of a true SAM position, integrating Bayesian estimation [22] with the bootstrap method [23] for generating additional data under various tactical scenarios.

2. Methods

According to the methodology in [5], the general formula for estimating the probability of destruction of a SAM system on the battlefield (as a component of SAM survivability) is as follows:

$$P_{kill} = P_d \cdot P_{id} \cdot P_l \cdot P_h \cdot P_{k/h}, \quad (1)$$

P_d – probability of detecting the SAM position;
P_{id} – probability of correct identification of the SAM position;
P_l – probability of launch (i.e., the adversary's decision to engage) against the SAM position;
P_h – probability of hit on the SAM position;
$P_{k/h}$ – probability that the SAM system becomes inoperative given a hit.
Based on this, the survivability estimate SAM is expressed as:

$$S = 1 - P_{kill}. \quad (2)$$

Within this approach, the probability of SAM destruction depends on a set of sequential events, among which one of the key stages is the correct identification of the true SAM position. In this paper, the subject of the study is specifically the informational component of this generalized methodology, namely P_{id}, i.e., the probability of correct identification of the SAM position. The other components of this methodology, including the characteristics of the adversary's strike assets, the influence of electronic warfare means, the temporal parameters of the strike, and other related factors, are considered beyond the scope of the present study. Accordingly, within the framework of this work, only the factor corresponding to the probability of correct identification of the SAM position is further detailed, whereas the remaining factors in formula (1) are treated as background or predefined parameters.

For assessing the survivability of surface-to-air missile systems under combat conditions, the information factor is

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of critical importance, as it directly affects the adversary's process of identifying SAM system positions. Modern means used for acquiring intelligence information include:

– satellites that conduct reconnaissance in optical and infrared bands, enabling detection of vehicle tracks or changes in the situation at positions. While satellites can distinguish decoy equipment with limited accuracy, repeated overpasses allow them to form recurring visual patterns;

– reconnaissance UAVs of short and medium range, often operating in pairs with strike UAVs to adjust or confirm SAM coordinates before an attack;

– electronic and signals intelligence for detecting active radar stations of SAM systems and creating a radar signature profile of the air defense system;

– long-range radars and airborne reconnaissance assets;

– reconnaissance in force through a decoy attack using kamikaze strike drones, which forces the SAM system to switch to active mode and subsequently allows for evaluating the effectiveness of air defense (whether it destroys the target or not, based on analysis of trajectories and missile–target intersection points).

The use of all available reconnaissance assets makes it possible to repeatedly verify data and identify SAM system positions while taking into account information that is continuously updated. To complicate reconnaissance and reduce the probability of correct identification of the true SAM positions, the following measures are usually implemented:

– deployment of dummy (false) positions equipped with mock-ups that replicate the thermal, radar, and visual signatures of real SAM systems;

– frequent relocation of SAM units;

– application of radio and thermal signature management (camouflage);

– use of electronic warfare (EW) assets;

– information operations and deception, including the deliberate dissemination of false coordinates in open sources (or through controlled channels) and the simulation of air defense activity in areas without actual deployment.

Given the use of comprehensive reconnaissance assets on the one hand and counter-reconnaissance measures on the other, under real combat conditions, information regarding the true SAM position is generally incomplete or uncertain. Therefore, periodic updating of reconnaissance data is essential for the adversary's correct identification of SAM positions.

Under the conditions of modern warfare, in order to ensure a more adequate assessment of the correctness of SAM position identification and, more generally, SAM survivability, it is of interest to take into account both the presence of counter-reconnaissance measures on one side and the adversary's repeated comprehensive reconnaissance of the true position on the other. In what follows, the analysis is focused specifically on the influence of false SAM positions on the assessment of the probability of correct identification of the true SAM position.

For the physical interpretation of the proposed model, it is appropriate to consider a notional position area within which one of the positions is true, while the others are false. The true and false positions are treated not merely as geometrically separated points, but as objects generating a set of observable features by which the adversary may identify them on the basis of repeated reconnaissance. Such features may include: optical; infrared; radar; engineering and fortification-related; and other revealing or simulated features that may potentially affect the correctness of position identification.

The true position is generally characterized by a more complete and stable set of features associated with system operation and combat deployment, whereas false positions reproduce these features only partially, selectively, or by simulation. In particular, false positions may include elements of optical, infrared, and radar masking, engineering preparation, decoy means, as well as other components intended to create the adversary's perception of a genuine firing position. In the general case, it is precisely the degree of similarity between the features of a false position and those of the true one that determines the probability of misidentification and affects the values of the conditional probabilities of feature observation within the Bayesian model.

The above factors, namely the composition of the combat layout elements, the spatial arrangement of positions, and the temporal modes of employment of deception means, are incorporated in a generalized manner through empirical conditional probabilities of observing authenticity-related features for each hypothesis regarding the existence of the true position. Such an approach makes it possible, without fixing a specific tactical configuration, to represent the influence of the combined effects of camouflage, engineering preparation, and deception on the adversary's process of identifying the true position

To model and assess the probability of correct identification of the true SAM system position, let us assume that:

– the adversary is assumed a priori to know with certainty that a true SAM position exists within the position area;

– repeated reconnaissance of the positional area in which the true SAM system position may be located is conducted using all available assets.

The assessment of the probability that a detected SAM system position is genuine will be carried out depending on the available information. The probability that a detected SAM position is the true one is understood here as the probability that a true position exists within the position area, while the adversary is unable to determine which of the j - positions, including the false ones, is the true position, $j \in \{1; N\}$.

By updated information we mean information that is obtained repeatedly from reconnaissance data after it has been known in advance that a true position exists within the positional area.

Given that updated information on the existence of a true SAM position is proposed to be used in calculating the probability of correct identification of a SAM position the application of a Bayesian approach for estimating this probability is appropriate. The Bayesian approach makes it possible to:

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– combine a priori information on the existence of the true position with updated information (new reconnaissance data);

– dynamically change the confidence in the authenticity of the SAM system position;

– make decisions on conducting a repeated strike;

– integrate uncertainty and false observations into the assessment.

Bayes' formula for calculating the posterior probability that position is a true one, taking into account updated information is as follows:

$$P_{(G_i/O)} = \frac{P_{(O/G_i)} \cdot P_{(G_i)}}{\sum_j P_{(O/G_j)} \cdot P_{(G_j)}}, \quad (3)$$

G_i – is the hypothesis that position i is the true one;
G_j – is the hypothesis that position j is the true one;
$P_{(Gi)}$ – is the prior probability that position i is the true one. That is, according to previously obtained information, it is known that there exists one true position in the positional area among a set that also includes decoy positions;
$P_{(O/Gi)}$ – is the probability of observing features - O if the detected position i is the true one. That is, if the position is true, it will exhibit certain features, such as strong radar emissions, thermal signatures, optical data, etc.;
$P_{(Gj)}$ – is the prior probability that position j is the true one;
$P_{(O/Gj)}$ - is the probability of observing the features if the detected position j is the true one.

Since the probability of correct identification of a SAM position is the posterior probability that the detected position is the true one, i.e. $P_{id} = P_{(Gj/O)}$, the general formula (1) for the P_{kill} assessment model will take the following form:

$$P_{kill} = P_d \cdot P_{(G_j/O)} \cdot P_l \cdot P_h \cdot P_{k/h}. \quad (4)$$

In this regard, it is of interest to assess the probability that a detected SAM system position is genuine for two cases:

1. Prior-only: only a priori information that exactly one of the candidate positions is genuine.

2. Updated information: availability of observation(s) and Bayesian updating.

To compare the effect of the number of false positions on the probability that a detected SAM system position is genuine, three scenarios of the positional area configuration will be considered:

1. Two positions (A, B), exactly one is genuine.

2. Three positions (A, B, C), exactly one is genuine.

3. Four positions (A, B, C, D), exactly one is genuine.

Let us define the set of hypotheses regarding the authenticity of positions:

$G = \{G_A, G_B, G_C, G_D\}$;

G_j – denotes that position is genuine, for $j \in \{A, B, C, D\}$.

Let it be assumed that the presence of a true SAM system position within the deployment area has been established a priori.

According to the first case, when only prior information is available, the probability that a detected SAM system position is genuine, under the condition that all positions observed within the positional area have the same probability of detection, is estimated identically for all scenarios using the following expression:

$$\hat{P}_{(G_A)} = \hat{P}_{(G_B)} = \hat{P}_{(G_C)} = \hat{P}_{(G_D)} = \frac{1}{N}. \quad (5)$$

It follows that the probability that a detected SAM system position is genuine depends exclusively on the number of positions present in the positional area.

Under the second approach, to account for updated information obtained from repeated reconnaissance, Bayes' formula is applied. Bayesian inference is performed for each hypothesis G_i regarding the authenticity of position i. For clarity of presentation, the subsequent calculations are first provided for hypothesis G_A , the estimates for the other positions are obtained analogously by permuting the corresponding conditional probabilities.

Assume that, based on repeated reconnaissance with a sample size of m=20, empirical counts of observed features (in the amount n) were obtained, indicating that when the true position is j, the adversary identifies position A as genuine. Then, the estimates of the conditional probabilities that the adversary identifies position A as the true one under different hypotheses are calculated using the following expressions:

$$\hat{P}_{(O_A/G_A)} = \frac{n_A}{m}, \quad \hat{P}_{(O_A/G_B)} = \frac{n_B}{m},$$
$$\hat{P}_{(O_A/G_C)} = \frac{n_C}{m}, \quad \hat{P}_{(O_A/G_D)} = \frac{n_D}{m},$$

n_A, n_B, n_C, n_D – the corresponding numbers of observations of features indicating the authenticity of position A, under the conditions that the true position is one of the respective positions A, B, C, or D.

Accordingly, table 1 (as an example) presents the empirical counts of observed features and estimates of the conditional probabilities of identifying position A under different hypotheses regarding the true position.

Taking into account expressions (3) and (5), using the Bayesian approach, the posterior estimate of the probability that the adversary identifies position A as the true one (for the third scenario) is given by:

$$\hat{P}_{(G_A/O_A)} = \frac{\hat{P}_{(O_A/G_A)} \cdot \hat{P}_{(G_A)}}{\hat{P}_{(O_A/G_A)} \cdot \hat{P}_{(G_A)} + \hat{P}_{(O_A/G_B)} \cdot \hat{P}_{(G_B)} + \hat{P}_{(O_A/G_C)} \cdot \hat{P}_{(G_C)} + \hat{P}_{(O_A/G_D)} \cdot \hat{P}_{(G_D)}} \quad (6)$$

When making a decision regarding position A, and taking into account after substituting the initial data, we get:

$$\hat{P}_{(G_A/O_A)} = 0.394$$

According to the first variant, in accordance with formula (5), with equal a priori probabilities for all positions, the estimated probability that one of the detected positions is the true one (for the third scenario) is equal to:

$$\hat{P}_{(G_A)} = \hat{P}_{(G_B)} = \hat{P}_{(G_C)} = \hat{P}_{(G_D)} = \frac{1}{N} = 0.25$$

From the calculation results, it can be seen that the use of the Bayesian estimate, which accounts for updated

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information regarding the true position, yields a higher value of the probability that the detected position is genuine.

Similarly, using expression (6), the probability that one of the detected positions is the true one relative to the other positions is calculated. For example (in the third scenario), the posterior estimate of the probability that position C is the true one, given that the observation (decision) was erroneously attributed to position A, is calculated using the following expression:

$$\hat{P}_{(G_C/O_A)} = \frac{\hat{P}_{(O_A/G_C)} \cdot \hat{P}_{(G_C)}}{\hat{P}_{(O_A/G_A)} \cdot \hat{P}_{(G_A)} + \hat{P}_{(O_A/G_B)} \cdot \hat{P}_{(G_B)} + \hat{P}_{(O_A/G_C)} \cdot \hat{P}_{(G_C)} + \hat{P}_{(O_A/G_D)} \cdot \hat{P}_{(G_D)}} \quad (7)$$

Table 1. – Empirical counts of observed features and estimates of the conditional probabilities of identifying position A under different hypotheses regarding the true position (for m=20 observations)

Number features indicating the authenticity of position A(n)	Probability estimate	Notation	Interpretation of probability
n_A=15	0.75	$\hat{P}_{(O_A/G_A)}$	the probability that, given position A is the true one, the observation result will be attributed specifically to position A
n_B=11	0.55	$\hat{P}_{(O_A/G_B)}$	the probability that, given position B is the true one, the observation result will be attributed to position A (i.e., if position B is the true one, there is a 0.55 probability that the reconnaissance or identification procedure will erroneously indicate position A as the true one)
n_C=7	0.35	$\hat{P}_{(O_A/G_C)}$	the probability that, given position C is the true one, the observation result will be attributed to position A (i.e., if position C is the true one, there is a 0.35 probability that the reconnaissance or identification procedure will erroneously indicate position A as the true one)
n_D=5	0.25	$\hat{P}_{(O_A/G_D)}$	the probability that, given position D is the true one, the observation result will be attributed to position A (i.e., if position D is the true one, there is a 0.25 probability that the reconnaissance or identification procedure will erroneously indicate position A as the true one)

The obtained estimate of the probability that the detected position is genuine, derived using the Bayesian approach, is a point estimate obtained from a single sample consisting of m observations. Therefore, in order to account for the uncertainty associated with the limited sample size, it is advisable to generate a set of alternative resamples, to each of which the Bayesian estimation of the authenticity of the SAM position is applied. To assess the uncertainty of the posterior Bayesian estimates, a nonparametric bootstrap method [23] was used, based on resampling with replacement from the original binary observation samples.

The algorithm for generating bootstrap samples to estimate the posterior probabilities is as follows:

1. For each hypothesis G_j, the initial observation results of the features are represented as a binary sample of size m :

$$n_{O/j} = (x_1, x_2 \dots x_m),\ x_k \in \{0,1\}, \quad (8)$$

where x_k=1 indicates that in the k-th observation ($k=1,2\dots m$), features were recorded that point to the position being true (in the example, position A);
x_k=0 indicates the absence of such features.

2. For each of the initial binary samples, at the b-th iteration of the bootstrap procedure ($b=1,2\dots M$), a pseudo-sample of the same size m is generated by randomly sampling with replacement:

$$n^{*(b)}_{O/j} = \left(x_1^{*(b)}, x_2^{*(b)} \dots x_m^{*(b)}\right). \quad (9)$$

3. For each generated pseudo-sample, the estimate of the conditional probability of observing features indicating the true position under hypothesis G_j is calculated as the proportion of positive observations:

$$\hat{P}^{*(b)}_{(O/G_j)} = \frac{1}{m}\sum_{k=1}^{m} x_k^{*(b)}. \quad (10)$$

4. The estimates $\hat{P}^{*(b)}_{O/G_j}$ obtained at the b-th iteration are substituted into Bayes' formula to calculate the posterior probability that the detected position is the true one. For example, in the third scenario, for the hypothesis that position A is the true one, the posterior estimate at the b-th iteration is given by:

$$\hat{P}^{(b)}_{(G_A/O_A)} = \frac{\hat{P}^{(b)}_{(O_A/G_A)} \cdot \hat{P}_{(G_A)}}{\hat{P}^{(b)}_{(O_A/G_A)} \cdot \hat{P}_{(G_A)} + \hat{P}^{(b)}_{(O_A/G_B)} \cdot \hat{P}_{(G_B)} + \hat{P}^{(b)}_{(O_A/G_C)} \cdot \hat{P}_{(G_C)} + \hat{P}^{(b)}_{(O_A/G_D)} \cdot \hat{P}_{(G_D)}}. \quad (11)$$

5. After performing M-iterations, an empirical distribution of the posterior estimates is formed:

$$\left\{\hat{P}^{(1)},\ \hat{P}^{(2)}, \dots\ \hat{P}^{(M)}\right\}. \quad (12)$$

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Based on this distribution, for each position, the mean value, standard deviation, and confidence interval of the estimates are calculated in the form of a 95% interval with a lower confidence bound (LCB) and an upper confidence bound (UCB) for each position.

3. Results

Table 2 below presents the simulation results in the form of probability estimates that the detected position is genuine for each position, obtained using Bayesian estimates and the bootstrap method for three scenario variants. In the table, the following evaluation results are calculated and presented:

MP_G - the mean value of the probability that the detected position is genuine (when assessing the authenticity of each of the positions A, B, C, and D);

σP_G - the standard deviation;

LP_G, UP_G - the lower confidence bound (LCB) and upper confidence bound (UCB) of the probability that the detected position is genuine (when assessing the authenticity of each of the positions A, B, C, and D);

$\Delta P_G = UP_G - LP_G$ - the interval width;

$\Delta RP_G = \frac{\Delta P_G}{MP_G}$ - the relative interval width;

$CVP_G = \frac{\sigma P_G}{MP_G}$ - the coefficient of variation.

Table 2. – Results of modeling

Positions	Results of the assessment						
	MP_G	σP_G	LP_G	UP_G	ΔP_G	ΔRP_G	CVP_G
			1. Scenario - A,B				
A	0.58	0.06	0.462	0.7	0.238	0.411	0.107
B	0.42	0.058	0.304	0.538	0.234	0.552	0.138
			2. Scenario - A,B,C				
A	0.454	0.054	0.351	0.571	0.2	0.485	0.12
B	0.334	0.055	0.216	0.438	0.222	0.663	0.166
C	0.212	0.055	0.1	0.317	0.217	1.024	0.262
			3. Scenario - A,B,C,D				
A	0.397	0.051	0.3	0.5	0.2	0.5	0.129
B	0.292	0.048	0.189	0.382	0.19	0.66	0.173
C	0.183	0.047	0.088	0.277	0.18	1.02	0.262
D	0.13	0.048	0.033	0.227	0.19	1.48	0.36

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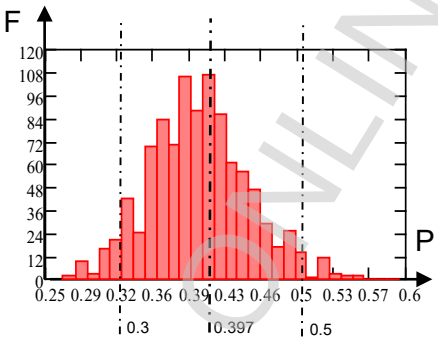


Figure 1. Histogram A

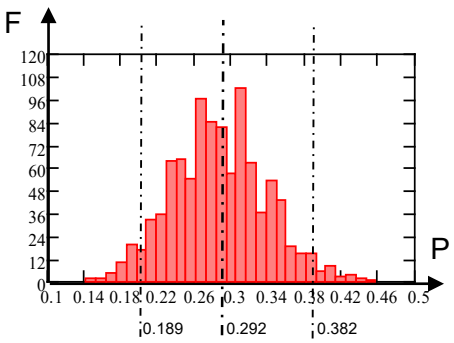


Figure 2. Histogram B

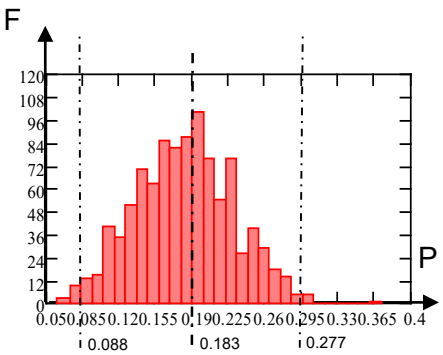


Figure 3. Histogram C

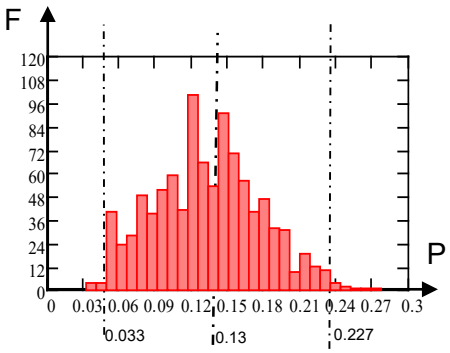


Figure 4. Histogram D

Below are figures presenting graphs in the form of histograms of the frequency distributions of the estimates that the detected positions are genuine (for the third scenario), with two-sided intervals bounded by the 2.5% quantile and the 97.5% quantile:

– figure 1: histogram of the frequency (F) distribution of probability (P) estimates of the authenticity of the position A is genuine (Histogram A). The distribution was obtained by generating 1000 samples based on 20 observations (m=20) from the initial binary sample of size n_A=15;

– figure 2: histogram of the frequency (F) distribution of the probability (P) estimates that position B is genuine (Histogram B). The distribution was obtained by generating 1000 samples based on 20 observations (m=20) from the initial binary sample of size n_B=11;

– figure 3: histogram of the frequency (F) distribution of the probability (P) estimates that position C is genuine (Histogram C). The distribution was obtained by generating 1000 samples based on 20 observations (m=20) from the initial binary sample of size n_C=7;

– figure 4: histogram of the frequency (F) distribution of the probability (P) estimates that position D is genuine (Histogram D). The distribution was obtained by generating 1000 samples based on 20 observations (m=20) from the initial binary sample of size n_D=5.

4. Discussion

The results of the modeling across the three scenarios yield the following conclusions.

1. Absence of updated information.

Under conditions of the absence of updated information, when applying the traditional approach, the estimated probability that the detected position is genuine is the same for all positions and depends only on their number.

2. Application of a combined approach.

The integration of Bayesian inference with bootstrap resampling allows the incorporation of updated reconnaissance information, thereby improving both the robustness and reliability of the estimates. For example, for the third scenario, the highest probability that the detected position is genuine corresponds to position A, with an estimated mean value of 0.397. However, taking into account the confidence interval, there is a non-negligible probability (approximately 0.6) that, under the condition that the true position is one of the other positions (B, C, or D), position A may be incorrectly selected as the genuine one.

3. Interval estimates and histogram analysis.

The results of interval estimation and frequency distribution histograms indicate the following.

When estimating the probabilities that the detected position is genuine for each of the four positions (A, B, C, and D), the relative width of the 95% confidence intervals (defined as the ratio of the interval width to the mean value) depends significantly on the frequency of correct detection in the initial sample. In particular, for position A, which is characterized by a high value of the initial binary sample, the relative width of the 95% confidence interval is 0.5 (50%), whereas for position D, which has a low value of the initial binary sample, this width is 1.48 (148%).

It can be observed that although the confidence interval for position A is somewhat wider in absolute terms (0.2) compared to position D, the relative width of this interval for position D exceeds the mean value by a factor of 1.5, indicating a higher uncertainty of the estimate. In addition, position A is characterized by a low coefficient of variation (0.129), which indicates high robustness of the model to data fluctuations. In contrast, for position D the coefficient of variation is 0.36, which indicates a high sensitivity of the model to changes in the sample. This confirms the importance of high-quality input data for ensuring the reliability of estimates within the Bayesian analysis framework.

4. Comparison of two approaches.

If the probabilities that a detected position is genuine are evaluated using formula (5) with fixed, a priori specified probability values, underestimated estimates of the probability of detecting the true position may be obtained. For example, for the third scenario, the probability that the detected position is genuine in the presence of four positions may be equal to 0.25. At the same time, when applying the Bayesian approach with the generation of pseudo-sample observation datasets, the estimated probability that the detected position is genuine may reach 0.397 (for the third scenario with respect to position A). However, a certain degree of uncertainty in the estimation should be taken into account. It is quite likely that during combat operations measures will be implemented to increase the concealment of the main SAM system positions through the use of decoy positions.

Therefore, it is advisable to incorporate the detection probability estimates of genuine positions into the classical survivability assessment methodology based on P_{kill}. Specifically, the probability of correct identification in formula (1) should be replaced with the Bayesian-bootstrap estimate of detecting the genuine position. The proposed model thus integrates logically with the P_{kill}, framework, which is widely applied in NATO operational planning.

The proposed approach makes it possible to simulate the process by which an adversary identifies SAM system positions in the absence of precise information about its algorithms or intelligence sources. Based on simulated data on observable features of genuine and decoy SAM positions, probabilistic models are constructed for each hypothesis (positions A, B, C, and D). The application of Bayes' theorem enables reproduction of the conditional process of updating the adversary's assessments after each observation, while the bootstrap method allows the impact of data fluctuations on these assessments to be evaluated. As a result, a range of possible estimates of the probability that a detected position is genuine is modeled for each position. This provides a basis for forecasting adversary actions and for developing measures aimed at deceiving the adversary.

5. Conclusion

Under combat conditions, an important factor in assessing the survivability of SAM systems is the informational factor, which affects the correctness of identifying SAM system positions. Under conditions where adversary reconnaissance is countered on one side, while multiple reconnaissance passes of SAM deployment areas are possible on the other, it becomes essential to assess and incorporate the impact of updated information on the authenticity of SAM positions. Application of the traditional approach, which considers only a priori information on the existence

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of a genuine position within the deployment area, proves inadequate and tends to produce overly optimistic expectations concerning the effectiveness of deception measures against enemy reconnaissance.

For a qualitative and reliable assessment of the probability that a detected position is genuine, it is proposed to apply a Bayesian approach combined with the bootstrap method for generating multiple observation datasets. This makes it possible to obtain confidence bounds for the probabilities and to assess the correctness of position identification under uncertainty. In addition, the application of scenario analysis enables the estimation of minimum and maximum values of the probabilities that detected positions are genuine, which should be taken into account when modeling the survivability of SAM systems.

Overall, the probabilistic model proposed in this study for assessing the probability that a detected position is genuine, based on the Bayesian approach and the bootstrap method, has direct practical relevance for planning and optimizing camouflage and deception measures. The obtained estimates make it possible to determine the level of camouflage, identify positions with an increased risk of disclosure, and evaluate the effectiveness of measures aimed at reducing the probability of position detection. To improve the reliability of probability estimates that a detected position is genuine, it is advisable to conduct field experiments in rear areas by creating a notional positional area with several decoy positions and performing repeated reconnaissance of the genuine position. This would allow the formation of initial observation samples, with the registration of misclassification errors for decoy and genuine positions, and the development of an empirical basis for further approximation of probabilities in Bayesian assessment models.

In this study, the assessment of the probability that one of the detected positions is genuine is considered from the defensive perspective. The model does not fully describe potential adversary behavior, since the actual intelligence data available to the adversary are unknown. In particular, the adversary may have only a single set of observations under conditions where the genuine position is known only to them, which requires separate modeling. The modeling results may be used as a tool for the quantitative substantiation of measures aimed at improving the survivability of SAM systems under uncertainty.

Potential directions for future research include:

– conducting field experiments in rear areas involving the deployment of a notional SAM deployment area comprising one true position and several decoy positions, with repeated reconnaissance by different sensor and intelligence assets to generate empirical observation datasets;

– extending the model toward sequential multi-stage Bayesian updating after each reconnaissance cycle, including analysis of the consequences of strikes against the detected SAM position, thereby enabling the dynamics of adversary information accumulation over time to be taken into account;

– extending the model to assess the influence of electronic warfare countermeasures on both the probability of detecting a SAM position and the probability of its correct identification;

– incorporating the effects of specific camouflage and deception measures, including optical, infrared, and radar concealment, field fortification of positions, as well as different operating modes of radar emission simulators;

– developing a probabilistic position-identification model aimed at minimizing the posterior probability of correct identification of the true position based on unmasking features in the presence of multiple decoy positions.

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References

[1] Watling J., Reynolds N., 2025. Tactical Developments During the Third Year of the Russo-Ukrainian War, Royal United Services Institute (RUSI) Special Report. [Online]. Available at: https://static.rusi.org/tactical-developments-third-year-russo-ukrainian-war-february-2205.pdf [Accessed: 4 April 2026].

[2] Rivero J.L., 2024. Decoy Warfare: Lessons and Implication from the War in Ukraine, Proceedings, 150(4). [Online]. Available at: https://www.usni.org/magazines/proceedings/2024/april/decoy-warfare-lessons-and-implication-war-ukraine [Accessed: 4 April 2026].

[3] Ryan M., Singer P.W., 2025. The Future of Deception in War: Lessons from Ukraine, New America Future Security Report. [Online]. Available at: https://www.newamerica.org/future-security/reports/the-future-of-deception-in-war/ [Accessed: 9 April 2026].

[4] Watling J., Sylvia N., 2025. Competitive Electronic Warfare in Modern Land Operations, Royal United Services Institute (RUSI) Occasional Paper. [Online]. Available at: https://static.rusi.org/competitive-electronic-warfare-in-land-operations_1.pdf [Accessed: 9 April 2026].

[5] Ball R.E., 2003. The Fundamentals of Aircraft Combat Survivability Analysis and Design, Second Edition, AIAA Education Series, American Institute of Aeronautics and Astronautics (AIAA). [Online]. Available at: https://arc.aiaa.org/doi/book/10.2514/4.862519 [Accessed: 9 April 2026].

[6] Blackman S.S., Popoli R.F., 1999. Design and Analysis of Modern Tracking Systems, Artech House, Norwood, MA. ISBN: 978-1580530064.

[7] Duda R.O., Hart P.E., Stork D.G., 2001. Pattern Classification, 2nd Edition, Wiley-Interscience, New York. ISBN: 978-0471056690.

[8] NATO Standardization Office, 2021. NATO Glossary of Terms and Definitions (AAP-06), NATO Standardization Office, Brussels. [Online]. Available at: https://nso.nato.int (restricted access) [Accessed: 9 April 2026].

[9] NATO Science and Technology Organization (STO), 2018. Survivability and Vulnerability Assessment of Air and Missile Defense Systems, RTO Technical Report TR-SET-180, NATO STO, Neuilly-sur-Seine, France.

[10] Tuncer O., Çırpan H.A., 2023. Adaptive fuzzy based threat evaluation method for air and missile defense systems, Information Sciences, 643, 119191. doi: https://doi.org/10.1016/j.ins.2023.119191

[11] Han Q., Pang B., Li S., Li N., Guo P.-s., Fan C.-l., Li W.-m., 2023. Evaluation method and optimization strategies of resilience for air & space defense system of systems based on kill network theory and improved self-information quantity, Defence Technology, 21, 219–239. doi: https://doi.org/10.1016/j.dt.2023.01.005

[12] Chen Z., Hong D., Cui W., Xue W., Wang Y., Zhong J., 2023. Resilience evaluation and optimal design for weapon system of systems with dynamic reconfiguration, Reliability Engineering & System Safety, 237, 109409. doi: https://doi.org/10.1016/j.ress.2023.109409

[13] Dachkovskyi V., 2020. Method of determination of survival characteristics of weapons and military equipment, Social Development and Security, 10(1), 18–24. doi: https://doi.org/10.33445/sds.2020.10.1.3

[14] Mehelbei V.V., Lezik O.V., Babych V.Yu., Romenskyi D.S., 2021. Metodyka otsiniuvannia zhyvuchosti ozbroiennia zenitnoho pidrozdilu (chastyny) [Methodology for assessing the survivability of anti-aircraft unit (subunit) weapons], Systemy ozbroiennia i viiskova tekhnika,

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1(65), 36–41. Ukrainian. doi: https://doi.org/10.30748/soivt.2021.65.05
[15] Stakh T., Sidor R., Khaustov D., Khaustov Ya., Kyrychuk O., Mudryk V., Nastyshyn Yu., 2025. Uzahalnena model zhyvuchosti zrazkiv bronetankovoho ozbroiennia i tekhniky [Generalized model of survivability of armored weapons and equipment samples], Viiskovo-tekhnichnyi zbirnyk, 32, 28–43. Ukrainian. doi: https://doi.org/10.33577/2312-4458.32.2025.28-43
[16] Hloba O., Levchenko M., 2022. Praktychni rekomendatsii shchodo pidvyshchennia zhyvuchosti systemy zenitnoho raketnoho prykruttia v operatsiiakh Obiednanykh syl [Practical recommendations for improving the survivability of the surface-to-air missile coverage system in Joint Forces operations], Povitriana mits Ukrainy, 1(1(2)), 65–70. Ukrainian. doi: https://doi.org/10.33099/2786-7714-2022-1-1(2)-65-70
[17] Voluvach S.A., Voronin V.V., Rysovanyi O.M., Tretiak V.F., Balakireva S.M., 2024. Udoskonalennia pidkhodiv shchodo otsiniuvannia pokaznykiv zhyvuchosti pidrozdiliv zenitnykh raketnykh viisk [Improvement of approaches to assessing survivability indicators of anti-aircraft missile units], Systemy ozbroiennia i viiskova tekhnika, 1(77), 81–86. Ukrainian. doi: https://doi.org/10.30748/soivt.2024.77.11
[18] Otroshok S., 2025. Metodyka vyznachennia optymalnoi kilkosti fiktyvnykh startovykh pozytsii viiskovykh formuvan raketnykh viisk dlia zabezpechennia yikh zhyvuchosti v oboronnii operatsii [Methodology for determining the optimal number of dummy launch positions of missile troops units to ensure their survivability in a defensive operation], Collection of Scientific Papers "LOGOS", 116–123. Ukrainian. doi: https://doi.org/10.36074/logos-04.04.2025.023
[19] Kondratenko Ye., 2024. Udoskonalena metodyka otsiniuvannia zhyvuchosti artyleriiskykh pidrozdiliv u nastupalnomu boiu [Improved methodology for assessing the survivability of artillery units in offensive combat], Grail of Science, 39, 249–258. Ukrainian. doi: https://doi.org/10.36074/grail-of-science.10.05.2024.034
[20] Hohoniants S.Yu., Kryshchenko V.M., 2018. Metodyka otsiniuvannia zhyvuchosti uhrupovannia radiotekhnichnykh viisk pid chas uchasti u vidbytti udaru povitrianoho protyvnyka [Methodology for assessing the survivability of a grouping of radio-technical troops during the repulsion of an enemy air strike], Zbirnyk naukovykh prats Kharkivskoho natsionalnoho universytetu Povitrianykh Syl, 3, 8–13. Ukrainian. [Online]. Available at: http://nbuv.gov.ua/UJRN/ZKhUPS_2018_3_3 [Accessed: 9 April 2026].
[21] Kim, A., Lee, D., 2024. Dynamic Bayesian network-based situational awareness and course of action decision-making support model, Expert Systems with Applications, 252(A), 124093. doi: https://doi.org/10.1016/j.eswa.2024.124093
[22] Gelman A., Carlin J.B., Stern H.S., Dunson D.B., Vehtari A., Rubin D.B., 2013. Bayesian Data Analysis, 3rd ed., Chapman and Hall/CRC. doi: https://doi.org/10.1201/b16018
[23] Efron B., Tibshirani R., 1993. An Introduction to the Bootstrap, Chapman & Hall/CRC.

Bajesov model za identifikaciju stvarnih položaja zenitno-raketnih sistema u proceni preživljavanja

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Apstrakt

Uvod/Cilj: procena preživljavanja zenitno-raketnih sistema (ZRS) široko se sprovodi primenom metodologija zasnovanih na konceptu P_{kill} (verovatnoća uništenja) i njegovim izvedenim pokazateljima, usvojenim u praksi NATO-a. Jedna od ključnih komponenti ove metodologije jeste verovatnoća ispravne identifikacije položaja zenitno-raketnog sistema. Primena mera protivizviđanja, a naročito raspoređivanje lažnih položaja, unosi značajnu neizvesnost u proces identifikacije otkrivenih položaja. **Metode:** predložen je kombinovani pristup za procenu verovatnoće ispravne identifikacije položaja, koji integriše Bajesovo zaključivanje sa bootstrap metodom za generisanje dodatnih uzoraka podataka u različitim taktičkim scenarijima. Bootstrap uzorci se generišu iz početnih skupova podataka posmatranja za svaki položaj, što omogućava uključivanje kako apriornih informacija o postojanju stvarnog položaja, tako i ažuriranih informacija dobijenih ponovljenim izviđanjem. **Rezultati:** predloženi pristup obezbeđuje ne samo tačkaste procene verovatnoće ispravne identifikacije stvarnog položaja ZRS, već i odgovarajuće intervale poverenja, kao i ocenu robusnosti modela u odnosu na fluktuacije podataka. Rezultati pokazuju da su tradicionalni pristupi, koji se oslanjaju isključivo na apriorne informacije, nedovoljni i dovode do precenjenih očekivanja u pogledu efikasnosti mera protivizviđanja. **Zaključak:** razvijeni model omogućava simulaciju procesa identifikacije položaja ZRS od strane protivnika u uslovima odsustva pouzdanih informacija o njegovim algoritmima izviđanja ili izvorima obaveštajnih podataka. Radi povećanja pouzdanosti procena, preporučljivo je sprovesti terenske eksperimente u pozadinskim područjima, formiranjem uslovnog pozicionog rejona sa više lažnih položaja i izvođenjem ponovljenog izviđanja.

Originalni naučni rad,
matematika, efikasnost i preživljavanje naoružanja
Ključne reči:
preživljavanje;
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bootstrap metoda.

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